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RESEARCH ARTICLE

Motivational engine with autonomous sub-goal identification for the Multilevel Darwinist Brain

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Abstract
This work proposes a motivational system for an autonomous robot that guides the fulfillment of its goals in a developmental manner, discovering sub-goals not only as a way to simplify goal achievement, but as a way to acquire knowledge in an incremental, modular and reusable fashion. This system has been called MotivEn (Motivational Engine) and we have carried out its initial integration within the Multilevel Darwinist Brain (MDB) cognitive architecture. We describe here the main elements of MotivEn and how they improve the current MDB operation. Moreover, we present in detail a specific implementation of MotivEn and the application results obtained in terms of sub-goal identification when applying it in a real robot experiment with the MDB.

Introduction

The autonomous identification of sub-goals and how to combine them to achieve the main goals are open research issues in cognitive developmental robotics (CDR). In fact, this topic has been mainly studied within the reinforcement learning (RL) field with a low impact in CDR (Cangelosi & Schlesinger, 2015). Cognitive architectures in CDR are based, as opposed to classical symbolic approaches, on cognitive processing theories where the key feature is the emergence of cognitive capabilities through embodied interaction with the real world in an incrementally more complex fashion (Asada et al., 2009; Vernon, 2014). But this interaction is actually driven by the set of goals the robot must achieve during its lifetime (externally imposed or autonomously acquired). Consequently, decomposing these goals into sub-goals is a very relevant aspect in CDR to promote incremental robot development in terms of complexity and knowledge reuse.

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Most authors address the sub-goal identification problem through the analysis of the state space of the robot with the aim of recognizing relevant states that will be considered as interesting points the robot should achieve in its path to a goal. In this line, bottleneck points are described as regions of the search space that the agent frequently visits when a goal is successfully achieved (McGovern & Barto, 2001). Different approaches have been proposed for the identification of bottleneck points, mainly based on frequency or density analysis of the sensorimotor states. The discretization of the state space using different techniques and the analysis of the graphs that represent these spaces has been one of the main approaches proposed so far, mainly in the field of Reinforcement Learning (RL). Examples of these techniques where the authors analyze the graphs identifying the transitional states more frequently visited by the agents are: diverse density (McGovern & Barto, 2001), Q-cut dynamics (Menache, Mannor, & Shimkin, 2002), betweenness centrality (Simsek & Barto, 2007) or clustering (Mannor, Menache, Hoze, & Klein, 2004). Most of the work, however, is carried out over discrete valued states and papers that analyze continuous valued states are not very common. Two relatively recent attempts are those found in Konidaris and Barto (2008) and Salge, Glackin, and Polani (2013). In the former the authors used an incremental algorithm for the analysis of trajectories, called sensorimotor abstraction. In the latter, the authors present the concept of empowerment, which is defined based on the concept of mutual information through the identification of states in the sensorimotor space that maximize the future available information, that is, states that lead to new states that increase the knowledge the agent has about the sensorimotor space.

Once sub-goals have been identified, the problem is how to combine them to reach the main goal o goals. Due to a strong influence of RL, this has usually been addressed from the point of view of the skills (or options (Konidaris & Barto, 2007) as extensions of skills) necessary to reach the sub-goals in the form of skill chaining or skill composition and mostly in discrete domains. The approaches proposed are based on the theory of options or hierarchical reinforcement learning (Sutton, Precup, & Singh, 1999), which decompose larger problems into smaller and more computationally manageable problems that are then combined for the resolution of the entire problem. In Konidaris and Barto (2009), Konidaris and Barto propose a method for skill chaining in which the skills or options identified by their sensorimotor abstraction algorithm are combined by chaining these base skills leading to a more complete policy. In Thrun and Schwartz (1995), the authors presented SKILLS, an algorithm devoted to the combination of basic skills or options in a hierarchical manner. A similar approach is proposed in Pickett and Barto (2002), where the POLICYBLOCKS algorithm is based on the same principles as SKILLS. In their works the authors start with a set of handmade or previously created skills and through the analysis of the commonalities over different tasks in which the basic skills have been used, obtain higher level skills that can be reused in several tasks. The problem with most of these approaches is that they have generally considered discrete state spaces and they have not really addressed the generation of sub-goals, but rather of sub-skills and in most cases, not even that, as the sub-skills were hand coded and only their chaining was contemplated. In this paper we are interested in the autonomous identification of sub-goals for a developmental robot, so it is necessary to manage explicit representations of the goals that can be used to determine particular courses of action considering continuous domains, and address the identification of sub-goals and their concatenation in order to prospectively decide on the appropriate policies to achieve a final goal.

To address this problem, we propose here a motivational system for an autonomous robot that guides the fulfillment of its goals in a developmental manner, discovering sub-goals not only as a way to simplify goal achievement, but also as a way to acquire knowledge and skills in an incremental, modular and reusable fashion. This system has been called MotivEn (Motivational Engine) and we have performed an initial integration with the Multilevel Darwinist Brain (MDB) cognitive architecture (Bellas, Duro, Faina, & Souto, 2010). In this paper, we will show the first results obtained in terms of sub-goal identification when applying this integrated cognitive architecture in a real robot experiment.

Thus, the remainder of the paper has been organized as follows: Section 'A simplified Multilevel Darwinist Brain' contains a description of the main elements and operation of the MDB that are relevant for this work. Section 'MotivEn integration in the MDB' presents the MotivEn components and their preliminary integration with the MDB. Section 'First results with MotivEn' is devoted to the details of a specific implementation of MotivEn we have developed to show its validity in a practical case. Section 'Real Robot Experiment' contains the analysis of the results obtained in a real robotic experiment with a Baxter robot and, finally, Section 'Conclusions' presents the main conclusions that can be extracted from this work.

A simplified Multilevel Darwinist Brain

The Multilevel Darwinist Brain (MDB) is a cognitive architecture which fits into the CDR paradigm. A key feature of MDB is that of applying artificial evolution in the main learning processes that are carried out, taking inspiration from classical bio-psychological theories that relate the brain and its operation through a Darwinist process based on evolutionary concepts at different time scales (Bellas et al., 2010). The MDB has been tested in different robotic experiments and several improvements have been included in the last few years (Bellas, Caamaño, Faiña, & Duro, 2014; Duro, Bellas, Becerra, & Salgado, 2014). But here we will describe a simplified version of the MDB that includes only the elements that are required for this preliminary MotivEn integration.

Thus, the MDB basic operation can be defined in terms of:

- *Sensorial state (S):* an array of sensorial values in a given instant of time (raw values or more complex representations).
- *Action (A):* value provided to the robot actuators (from simple motor commands to more complex representations of actions).